

Research Paper

Disentangling the effects of climate and urban growth on streamflow for sustainable urban development: A stochastic approach to flow regime attribution

Tijana Jovanovic^{a,b}, Fengyun Sun^{a,c}, Tasnuva Mahjabin^a, Alfonso Mejia^{a,*}

^a Department of Civil and Environmental Engineering, The Pennsylvania State University, University Park, PA, USA

^b National Socio-Environmental Synthesis Center, Annapolis, MD, USA

^c School of Geographic Sciences, East China Normal University, Shanghai, China



ARTICLE INFO

Keywords:

Climate change
Urban planning
Stormwater management
Land cover
Environmental flows
Hydrology
Ecology

ABSTRACT

In urban watersheds, climate variability and change, urban growth, and stormwater management can act concurrently over time to shape and alter the streamflow dynamics. Yet, when assessing the impacts of urbanization on streamflow, these factors are rarely taken simultaneously into consideration. There is thus an emerging need for approaches that allow disentangling the hydrological impacts of land cover change from those due to climate, in the context of long-term, historical changes in urban landscapes. This is here termed flow regime attribution. We demonstrate in this study the ability of a stochastic mechanistic model to perform flow regime attribution. The modeling approach is applied to the Watts Branch watershed, located in metropolitan Washington D.C., United States. To carry out the flow regime attribution, the model is used to compute streamflow indicators of hydrological alteration and perform parameter sensitivity analysis. The application of the model shows that in Watts Branch urban growth drives the long-term temporal trend in streamflow. The mean and variance of streamflow increase at the end of the gauging period by 2 and 7 times, respectively, their value relative to an only climate (no urban growth) scenario. The results show that climate mainly amplifies or dampens the temporal trend according to wet/dry variations in annual rainfall. Further, the model facilitates the attribution process by allowing the derivation of streamflow indicators that directly depend on the model parameters. The proposed modeling approach may be useful for assessing the long-term flow behavior of urban watersheds, and informing sustainable urban development decisions.

1. Introduction

Urban sprawl has resulted in major environmental (Geneletti, La Rosa, Spyra, & Cortinovis, 2017; Johnson, 2001; Su, Gu, Yang, Chen, & Zhen, 2010; Vimal, Geniaux, Pluvinet, Napoleone, & Lepart, 2012; Wilson & Chakraborty, 2013) and human health (Frumkin, 2002) problems. It has brought substantial negative impacts to streams, floodplains, and riparian areas in urban watersheds (Martin-Mikle, de Beurs, Julian, & Mayer, 2015; Miltner, White, & Yoder, 2004; Sharley, Sharp, Marshall, Jeppe, & Pettigrove, 2017; Wu, Bolte, Hulse, & Johnson, 2015a; Wu, Stewart, Thompson, Kolka, and Franz, 2015b). The terms urban watershed and urbanization are used to indicate contemporary suburbanization, i.e., landscapes that have experienced significant urban growth after World War II. In addressing the negative impacts of urban sprawl on hydrological conditions, an emerging challenge is that of distinguishing the impacts associated with urbanization from those

due to climate variability and change in a particular watershed and time period (Bindoff et al., 2013; Gallo, Moore, & Wywrot, 2012; Pyke et al., 2011). This is here termed flow regime attribution (Bindoff et al., 2013; National Academies of Sciences, 2016). Separating the impacts of urbanization and climate on streamflow is crucial to inform urban stormwater planning and management decisions about the relative dominance of these two fundamental drivers of hydrological change. Misidentifying their relative dominance could result in stormwater management policy that are, over the long term, ineffective. For example, this could be the case in places where climate is a strong driver of hydrological change but policy may be geared towards mitigating landscape modifications alone.

It is well recognized that urbanization can have a dramatic impact on hydrological conditions (Leopold, 1968); less known is how urbanization interacts with climate variability and stormwater management conditions over time to shape and alter the flow regime. One reason for

* Corresponding author: 215B Sacket Building, University Park, PA 16802-1408, USA.

E-mail addresses: TVM5451@psu.edu (T. Mahjabin), amejia@engr.psu.edu (A. Mejia).

the latter is that impacts are typically studied within the context of recent or current landscape conditions. Indeed, a common approach is to rely on space-for-time substitution (Brown et al., 2009; Carter et al., 2009; Wu et al., 2015b), which consists of using several watersheds with varying levels of urban development, under current conditions, to represent a gradient of urban impacts. Space-for-time substitution necessarily makes assumptions about the temporal trends of urban landscape change (Carter et al., 2009). To avoid making such assumptions (e.g., that historical landscape trends can be captured by current landscape conditions), long-term temporal data and approaches must be used to determine the flow regime.

The flow regime is chosen as the target for attribution as it is a key driver of both abiotic and biotic stream conditions (Poff & Zimmerman, 2010; Postel & Richter, 2003). The flow regime paradigm is normally implemented through the use of streamflow indicators (Poff et al., 2010; Wu et al., 2015a). This can be particularly challenging in urban watersheds for two reasons. First, streamflow dynamics in urban watersheds are inherently nonstationary (Jovanovic, García, Gall, & Mejía, 2016a; Jovanovic, Mejía, Gall, and Gironás, 2016b) because, among other reasons, as watersheds urbanize over time runoff production typically increases. Second, climate variability and change can conflate the impacts of urbanization on streamflow. The latter can be accentuated by a reduction in the filtering capacity of the soil and subsurface watershed components, specifically through directly connected impervious areas (Roy & Shuster, 2009; Shuster, Pappas, & Zhang, 2008). Thus, long-term modeling of urban flow regimes must be able to handle nonstationarity.

It is also highly desirable that such models rely on readily available, long-term data. Long-term hydrometeorological and land cover data are most often available at the daily timescale (Mejía, Rossel, Gironás, & Jovanovic, 2015; Yang & Li, 2011). At the daily timescale the effects on hydrological conditions of urban stormwater features (e.g., stormwater sewer pipes and stormwater control measures such as detention ponds) are not explicitly resolved. The emphasis at this timescale is on the urban water budget and runoff volumes. This limits our ability to configure and verify highly resolved, spatially distributed hydrological models, suggesting the need for macroscopic models (e.g., spatially lumped or semi-distributed) that can capture the essential mechanistic features of urban watersheds (Wu et al., 2015a; Yang & Li, 2011). Further, decision making at the watershed level is often concerned with the overall trends and patterns that emerge over time (Yang & Li, 2011), where a macroscopic approach is suitable.

One approach to the macroscopic modeling of flow regimes is through stochastic mechanistic models (SMMs) (Basso, Schirmer, & Botter, 2015; Botter, Porporato, Daly, Rodriguez-Iturbe, & Rinaldo, 2007a; Botter, Porporato, Rodriguez-Iturbe, & Rinaldo, 2007b; Botter, Porporato, Rodriguez-Iturbe, & Rinaldo, 2009; Ceola et al., 2010). This class of parsimonious streamflow models have been used to study the dynamic interactions between streamflow and various factors, including climate variability (Botter, Basso, Rodriguez-Iturbe, & Rinaldo, 2013), landscape heterogeneity (Doulatyari et al., 2015), dams (Botter, Basso, Porporato, Rodriguez-Iturbe, & Rinaldo, 2010), and floods (Basso, Schirmer, & Botter, 2016). In essence, SMMs represent rainfall as a stochastic process in time and the watershed as a spatial unit capable of infiltrating rainfall and generating surface and/or subsurface runoff, while accounting for key climatic, landscape, and soil parameters. Recently, SMMs were extended to be applicable to urban watersheds (Mejía, Daly, Rossel, Jovanovic, & Gironás, 2014).

Our primary goal with this study is twofold. Firstly, to demonstrate the ability of the SMM to represent nonstationary streamflow dynamics over the long term in an urban watershed. Secondly, to demonstrate its ability to distinguish the influence of climate variability, urbanization, and stormwater management on streamflow. We believe the latter can be relevant and useful to scientists, landscape architects, planners, and engineers facing questions about flow regime attribution in urban watersheds. With ongoing and projected changes in climate, it is becoming

increasingly relevant to have quantitative tools that can help explain and explore the potential interactions between climate and urbanization. Such tools are needed to guide urban stormwater mitigation and adaptation actions, and enable tailored solutions to the concurrent stressors of climate and urbanization. The proposed SMM offers an approach to quantify the relative effects of urbanization and climate on flow regimes. The approach may be particularly useful for evaluating preliminary urban planning scenarios by maintaining the number of forcing variables and model parameters required to run the model to a minimum.

2. Modeling approach

2.1. Stochastic mechanistic model (SMM) of streamflow

The SMM simulates daily streamflow in an urban watershed while accounting for factors such as climate, land cover, soils, and stormwater management (Mejía et al., 2014). Note that hereafter we use the term SMM to denote the model by Mejía et al. (2014). Urban watersheds are represented as pervious areas and effective impervious areas that contribute at the watershed outlet baseflow and surface runoff, respectively. Ultimately, the daily streamflow simulated by the SMM consists of the addition of baseflow and surface runoff.

The SMM starts by assuming that the rainfall series, ξ , is a marked Poisson process with exponentially distributed rainfall depths Y (Fig. 1). Rainfall events occur with a frequency λ_R and have a mean magnitude $1/\gamma_R$. For the effective impervious areas in the watershed, excess rainfall ξ_I is generated from the rainfall series when the rainfall depth Y surpasses a threshold d_I ($Y > d_I$) and, for the pervious areas, subsurface recharge ξ_P is generated when $Y > d_P$ (Fig. 1). The subscripts I and P denote impervious and pervious landscape conditions, respectively. Hence, surface runoff is generated from the excess rainfall series ξ_I by rainfall falling on effective impervious areas, while subsurface recharge and baseflow are triggered by rainfall infiltrating into the soil (i.e., $Y > d_P$) in the pervious areas of the watershed. The thresholds d_I and d_P represent the capacity of the landscape to absorb rainfall. In addition, d_I and d_P are related to the mean frequency of effective urban runoff, λ_I , and subsurface recharge, λ_P , respectively, through the equation $\lambda_i = \lambda_R \exp(-d_i \gamma_R)$, where i can be equal to I or P . The derivation of this equation is demonstrated elsewhere (Mejía et al., 2014). Note that the model assumes the soil moisture storage behaves similarly in every event through evaporative losses. This assumption could be relaxed in the future to explicitly account for soil saturation following the approach by Bartlett, Daly, McDonnell,

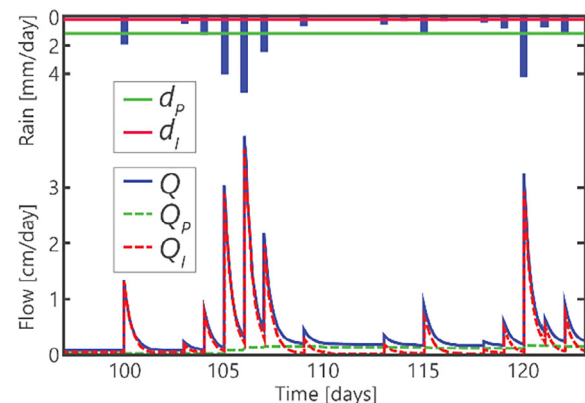


Fig. 1. Illustration of simulated rainfall and streamflow with the SMM. The definition of the variables in the plot is as follows: d_I and d_P are the thresholds above which surface runoff and subsurface recharge occur, respectively; Q_I and Q_P are the surface and subsurface flows, respectively; and $Q_I + Q_P$ is the total streamflow Q at the outlet of the watershed. The subscripts I and P indicate impervious and pervious conditions, respectively.

Parolari, and Porporato (2015).

Furthermore, in the SMM, the volume of surface runoff and baseflow generated are proportional to the effective impervious, AU^* , and pervious, $A(1 - U^*)$, areas in the watershed, respectively, where A is the area of the watershed and U^* the fraction of A that contributes to surface runoff. We use the equation $U^* = \beta U + \alpha$ to determine U^* (Mejía et al., 2015), where β and α are the fraction of impervious and pervious area, respectively, that directly contribute surface runoff to the outlet. In addition, to account for storage effects, the excess rainfall ξ_I and subsurface recharge ξ_P are subsequently assumed to be the input to a linear reservoir. A different reservoir is assumed for the effective impervious and pervious areas with mean response time $1/k_I$ and $1/k_P$, respectively. Note that the storage parameter for the effective impervious areas, $1/k_I$, embeds all the effects of artificial storage on surface runoff. Besides the parameter $1/k_I$, the SMM represents stormwater management conditions at the watershed level through the parameter β , which accounts for the effect of storm sewer pipes by quantifying the impervious areas directly connected to the outlet. Additionally, the parameter $A(1 - U^*)$ quantifies the ability of green (pervious) areas to enhance subsurface infiltration and reduce surface runoff.

The response or output from the impervious and pervious reservoir is then equal to the surface runoff Q_I and baseflow Q_P , respectively. Thus, the total streamflow Q at the outlet of the watershed is equal to $Q_I + Q_P$ (Fig. 1). Mathematically, the SMM is defined with the following stochastic differential equation:

$$\frac{dQ_I(t)}{dt} = -k_I Q_I(t) + k_I A \xi_I(t). \quad (1)$$

All the variables in Eq. (1) were previously defined, except l_i . l_i represents the land cover state of the watershed, which is equal to U^* and $1 - U^*$ for impervious and pervious conditions, respectively. Eq. (1) needs to be solved numerically via Monte Carlo simulation. It has, however, the advantage of allowing the determination of the exact statistical moments of streamflow as a function of the model parameters. The equations for the statistical moments of the total streamflow Q (i.e., the mean, $\langle Q \rangle$, variance, $\text{var}(Q)$, and skewness, $s(Q)$) are shown in the Appendix. Notice that, aside from the statistical moments of Q , one can compute from the streamflow simulated by the SMM different indicators of hydrological alteration. Fig. 2 uses a diagrammatic representation to summarize the modeling approach.

We use the SMM to assess the separate effects of urbanization and climate on streamflow by implementing the following steps. First, the model parameters are estimated using both the data and calibration. The calibration and application of the model is done by separating the observed streamflow data into nonoverlapping windows of equal duration (e.g., 4 years). The model is then applied to each window. Second, the model parameters and simulations are used to compute various streamflow indicators for different climate and urbanization scenarios. Third, parameter sensitivity analysis is performed by changing the value of the model parameters while keeping urbanization or climate constant. With the last two steps, we try to distinguish the effects of urbanization and climate on streamflow. The SMM is implemented in MATLAB.

2.2. Model parameter estimation

The SMM requires the estimation of eleven parameters. Most of the parameters (i.e., nine out of the eleven) can be obtained from readily available data. In this subsection we describe how to estimate the model parameters from available data while the actual value of the parameters used is presented and discussed in Section 4. All the model parameters and their physical meaning are summarized in Table 1. The climate parameters, λ_R and γ_R^{-1} , can be easily obtained from the analysis of daily rainfall data. For example, the parameter γ_R^{-1} is simply the mean rainfall depth for the rainy days in the data during a defined time period. The imperviousness parameter U can be obtained from

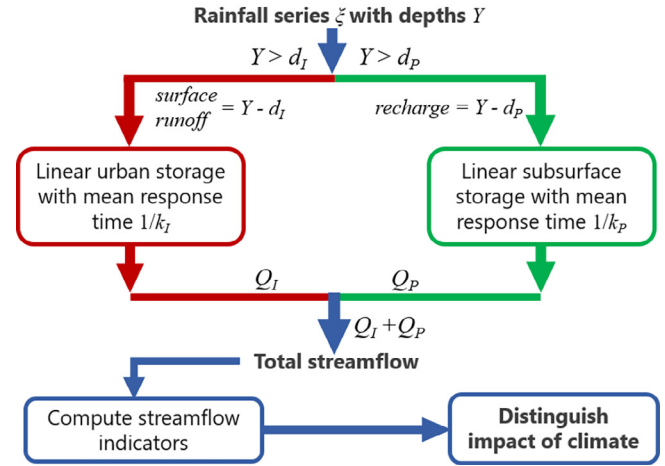


Fig. 2. Diagrammatic representation of the modeling approach used to perform the flow regime attribution for urban watersheds. The red arrows and box indicate impervious conditions and green pervious ones. The variables in the diagram are defined as follows: Y is the rainfall depth; d_I and d_P are the thresholds above which surface runoff and subsurface recharge occur, respectively; $1/k_I$ and $1/k_P$ are the mean response times of the urban and subsurface storage, respectively; Q_I and Q_P are the surface and subsurface flows, respectively; and $Q_I + Q_P$ is the total streamflow Q at the outlet of the watershed. The subscripts I and P indicate impervious and pervious conditions, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

historical maps and/or remote sensing data. In the U.S., remote sensing data are readily available for the last 20–40 years (Homer et al., 2015; Sleeter et al., 2013). The parameter U^* can be estimated from available information; sometimes regional equations are available for transforming U into U^* (Lee & Heaney, 2003; Roy & Shuster, 2009). The approach described by Mejía et al. (2015), which relies on calibration, was used in this study to find the values of the parameters β and α . The drainage area A can be obtained from digital elevation model data through standard Geographic Information System analysis.

The remaining four parameters (λ_I , k_I^{-1} , λ_P and k_P^{-1}) can be estimated as follows. The parameter λ_I can be assumed to be equal to λ_R , as the more realistic case of setting λ_I to be somewhat less than λ_R has little impact on the streamflow simulations (Mejía et al., 2014). This assumption means that all rainfall events contribute to surface runoff, even though in reality small events may contribute little or nothing as they can be handled by the initial storage capacity of the watershed. The parameter λ_P can be estimated using both the observed streamflow data and the equation for the mean streamflow, $\langle Q \rangle$, obtained from the SMM. Specifically, to estimate λ_P , one can set $\langle Q \rangle$ in Eq. A1 equal to the mean observed streamflow and then solve for λ_P . Lastly, the parameters k_I^{-1} and k_P^{-1} can be estimated via model calibration.

To calibrate the parameters k_I^{-1} and k_P^{-1} , we use the Nash-Sutcliffe efficiency index, computed using the log of the streamflow quantiles (LNSE), as the objective function:

$$LNSE = 1 - \frac{\sum_{j=1}^N [\log(Q_{o,j}) - \log(Q_j)]^2}{\sum_{j=1}^N [\log(Q_{o,j}) - \langle \log(Q_{o,j}) \rangle]^2}. \quad (2)$$

$Q_{o,j}$ and Q_j are the observed and estimated quantiles, respectively, for a given value of the exceedance probability, and N is the total number of quantiles considered (set here equal to 40). In Eq. (2), a value of $LNSE = 1$ indicates a perfect fit. To optimize Eq. (2), we use a non-linear optimization algorithm (Byrd, Hribar, & Nocedal, 1999).

2.3. Temporal nonstationarity

To account for temporal nonstationarity with the SMM approach,

Table 1
Summary of the model parameters.

Parameter	Dimensions (units)	Physical meaning
λ_R	T^{-1} (days $^{-1}$)	Mean frequency of rainfall or storm events
γ_R^{-1}	L (cm)	Mean depth or magnitude of rainfall events
U	Dimensionless (decimal percent)	Fraction of impervious area in the watershed
U^*	Dimensionless (decimal percent)	Fraction of effective impervious area in the watershed where $U^* = \beta U + \alpha$
β	Dimensionless (decimal percent)	Fraction of (calibrated) impervious area that contributes surface runoff to the watershed outlet
α	Dimensionless (decimal percent)	Fraction of (calibrated) pervious watershed area that contributes surface runoff to the outlet
A	L^2 (km ^{2})	Drainage area at the outlet of the watershed
λ_I	T^{-1} (days $^{-1}$)	Mean frequency of surface runoff events
k_I^{-1}	T (days)	Mean response time of the effective impervious areas. This parameter embeds the net effect of stormwater management on the hydrological response of the urban watershed
λ_p	T^{-1} (days $^{-1}$)	Mean frequency of subsurface recharge events
k_p^{-1}	T (days)	Mean response time of the subsurface flow or baseflow

we assume that climate and land cover conditions are approximately stationary over relatively short windows of time, e.g., 2- to 4-year windows. In this manner, according to the chosen window, the overall period of analysis is divided into nonoverlapping time windows of equal duration. Then, the SMM is applied (i.e., the model parameters are estimated) to each time window. This way of accounting for nonstationary has successfully been used before to account for changing climatic and landscape conditions in natural watersheds (Botter et al., 2013). It has not been used, as done in this study, to analyze the interactions between climate and urbanization as a function of time. By applying the model to each time window, we obtain the model parameter values as a function of time. We can then analyze how the parameter values change in time and perform model simulations, where the climate or urbanization parameters are fixed, to assess how urbanization and climate affect streamflow.

2.4. Streamflow indicators of hydrological alteration

Streamflow indicators, computed from time series data, are commonly used to assess hydrological alterations to the flow regime (Miltner et al., 2004; Wu et al., 2015a). Specifically, to quantify and characterize the impact of urbanization and climate variability on the flow regime, we select the following five streamflow indicators: mean, $\langle Q \rangle$, variance, $\text{var}(Q)$, and skewness, $s(Q)$, of streamflow; Hurst exponent, h ; and streamflow complexity measure, C (Jovanovic et al., 2016a; Jovanovic, Mejía, et al., 2016b; Poff et al., 2010). $\langle Q \rangle$, $\text{var}(Q)$, and $s(Q)$ are selected since these are familiar indicators commonly used to assess alterations to the flow regime, and because exact expressions for these indicators are available (see Appendix). The latter allows to explicitly relate the indicators to the SMM parameters. Additionally, we use $\text{var}(Q)$ to compute the streamflow flashiness (Baker, Richards, Loftus, & Kramer, 2004). Specifically, we use the ratio between $\text{var}(Q)$ and the predevelopment $\text{var}(Q)$, $\text{var}(Q_{\text{pre}})$, as an index of flashiness, where $\text{var}(Q_{\text{pre}})$ is computed based on the urbanization level at the beginning of the gauging period. The other two indicators, h and C , are considered here as they were recently found to outperform traditional indicators (Jovanovic et al., 2016a; Jovanovic, Mejía, et al., 2016b). h is a measure of the degree of correlation in a time series, typically between 0.5 and 1 for streamflow time series, with 0.5 indicating uncorrelated flow records (i.e., white noise) and 1 strongly correlated records (Kantelhardt et al., 2006). To estimate h from time series data, the same approach followed by Jovanovic, Mejía, et al. (2016b) is used, namely detrended fluctuation analysis (Kantelhardt et al., 2006). h tends to decline as urbanization increases (Jovanovic, Mejía, et al., 2016b) because, as a watershed becomes more urbanized, less of the daily rainfall falling on the watershed is filtered by the soil (subsurface) and daily rainfall tends to be weakly auto-correlated.

Likewise, the complexity measure C , which is a measure of the degree of organization or structure in a times series (Lamberti, Martin, Plastino, & Rosso, 2004; López-Ruiz, Mancini, & Calbet, 1995), is also

affected by the reduced filtering capacity of urbanized watersheds. C is computed as in Jovanovic et al. (2016a). C varies from 0 to 1, with 0 indicating little organization (e.g., a fully deterministic or purely random time series) and 1 a highly organized one (usually reserved for chaotic time series) (Lamberti et al., 2004). Relevantly, Jovanovic et al. (2016a) showed that C tends to decrease in urbanized watersheds, as streamflow tends to more closely resemble the randomness of the rainfall series as urbanization increases.

We use the SMM to compute the streamflow indicators. By changing the model parameter values, we compute indicators for different scenarios where the climate or urbanization parameters are fixed. We can then contrast the scenarios to assess how climate and urbanization separately influence streamflow. The SMM is particularly well suited for computing robust streamflow indicators by facilitating the simulation of long-term streamflow conditions for a set of parameter values. Because streamflow indicators are commonly used to assess stream health, the SMM provides a way for landscape and urban planners to develop preliminary assessments or explore the likely effects of urban growth and climate on stream ecohydrological conditions.

3. Case study and data

The Watts Branch watershed, located in northwest metropolitan Washington D.C. (Fig. 3), is selected as the case study. The watershed has a total drainage area of 9.58 km ^{2} and is currently built-out, with land use consisting mostly of residential suburban development, as well as some commercial, industrial, and institutional land uses (BayLand, 2015). Streams at many locations in the watershed have been severely degraded (BayLand, 2015; MCDEP, 2003). From 1950 to 2000, imperviousness in Watts Branch grew from ~ 2 to about 42% (nearly build-out conditions) (CRDPW, 2001). Prior to the 1950s, Watts Branch was predominantly rural.

Daily streamflow gauging (USGS gauge 01645200) for Watts Branch covers the period 1958–1987. We use here this 30-year period to implement the SMM. The percent imperviousness area during this period ranges from ~ 10 to 32%. The first stormwater management regulations relevant to Watts Branch were enacted in the 1980s (CRDPW, 2001), which consisted mostly of basic controls (detention facilities) for floods and sediments. Thus, the majority of the urbanization considered in this study is representative of urban areas directly connected, through stormwater sewer pipes, to the stream network. According to the Soil Survey Geographic Database (SSURGO) of the U.S. Natural Resources Conservation Service, soils in Watts Branch are mostly silt loam or loam (e.g., SSURGO mapunit 533621) with moderate to high infiltration rates, ~ 1.5 to 5 cm/hr. The geology of Watts Branch is characterized by deeply weathered schist. The vegetation in Watts Branch was initially cultivated farmland, as urban development grew, it largely transitioned to urban lawns. To represent daily rainfall, we used the NOAA's Global Historical Climatological Network gauge (USC00187705) closets to Watts Branch (Fig. 3). Since this gauge had missing values, $\sim 8\%$ of the

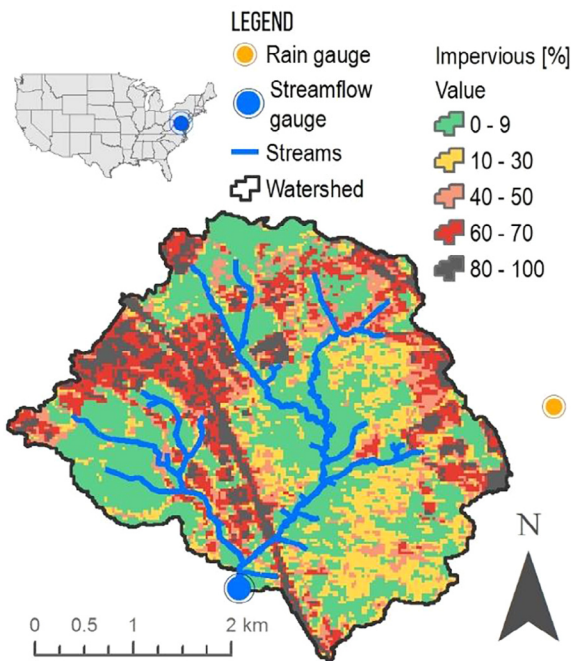


Fig. 3. Map illustrating the location, stream network, streamflow gauge, main rainfall gauge, and land cover (circa 2001) of the Watts Branch watershed. Note that the main rain gauge used lies outside the watershed boundary.

data, we used the average value from nearby gauges (USC00181125, USC00187272, USC00182325, and USC00181032) to determine rainfall for the days with missing data.

To account for urban growth, we use previously available, historical data representing urban land cover change over time (Mejía et al., 2015). The historical land cover data were previously derived from various sources, including tax maps, areal imagery, and remote sensing (Beighley and Moglen, 2003). The data classifies urban land cover into impervious and pervious areas. The latter are separated into forested or agricultural areas.

4. Results

4.1. Model performance

The SMM parameters values were obtained following the parameter estimation procedure outlined in Section 2.2. To illustrate and quantify the model performance, Fig. 4 plots the value of the $LNSE$ against time. The model parameters are estimated separately for the cool (Fig. 4a) and warm (Fig. 4b) season. These two seasons are used to present all of our results, with the cool season defined as the six months from October to March, and the warm one as April–September. Also, in Fig. 4, the parameters are estimated using both a 2- and 4-year time window. Recall that the time window defines the nonoverlapping sub-periods over which conditions are considered stationary for parameter estimation purposes. For example, in terms of the observed daily streamflow for a given season (cool or warm), the 2- and 4-year period include ~365 and 730 daily observations, respectively, for parameter estimation.

The performance of the model is overall quite satisfactory with $LNSE$ values around 0.95 for both the cool (Fig. 4a) and warm season (Fig. 4b). In general, the $LNSE$ estimates are more stable for the 4-year time window for both the cool and warm season, as the 4-year window allows using more data to estimate the parameters than the 2-year one. Thus, we use a 4-year time window for the remainder of our results. Note that for the 4-year time window the entire gauging period is divided into 7 sub-periods covering the years 1958–1985, the last three

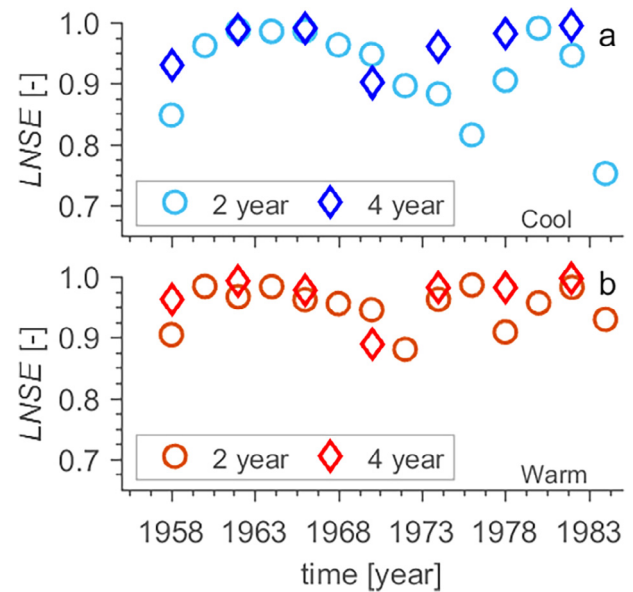


Fig. 4. Performance of the SMM simulations with respect to time for the (a) cool and (b) warm season. The performance is evaluated using both a 2- and 4-year time window when estimating the parameter values.

years of record, 1986–1988, are not considered. Relevantly, the performance of the SMM is reasonable using the $LNSE$, which is a performance metric that considers the entire range of flows, as opposed to emphasizing high flow events. This demonstrates that the SMM is suitable for modeling flow regimes in urban watersheds under nonstationary conditions. It indicates the SMM can provide reliable long-term information to urban planners and other stakeholders about the effects of urban growth, climate, and stormwater management on flow regimes.

4.2. Model parameter estimates

To analyze and explore the behavior of the model parameters, we plot the parameters λ_R , γ_R^{-1} , U , and U^* against time (Fig. 5). λ_R , γ_R^{-1} , U , and U^* represent the mean frequency of rainfall events, mean rainfall depth, fraction of impervious area, and fraction of effective impervious area, respectively (Table 1). The mean rainfall frequency λ_R varies between 0.18 and 0.39 days⁻¹ and the average value, ~0.29, is similar between the warm and cool season (Fig. 5a). The latter means that, on average, ~29% of all days in a given year are rainy days. The mean rainfall depth γ_R^{-1} varies between 0.73 and 1.18 cm and is on average somewhat greater in the warm season, ~1.04 cm, than in the cool one, ~0.89 cm (Fig. 5b).

A notable feature of Fig. 5a is that the cool season values of λ_R are lower during the first 3 sub-periods (i.e., from 1958 to 1969) than in the remaining years. This can also be seen when plotting the mean annual rainfall, $\langle R \rangle$, against time (Fig. 5c). The mean annual rainfall is estimated as $\langle R \rangle = 365\lambda_R\gamma_R^{-1}$. The advantage of using $\langle R \rangle$ to assess dry or wet conditions is that it simultaneously accounts for the effect of both rainfall parameters, λ_R and γ_R^{-1} , on watershed climatology. For the cool season, Fig. 5c shows that the first 3 sub-periods (years 1958–1969), together with the sub-period 1978–1981, have the lowest values of $\langle R \rangle$. Indeed, based on annual historical departures from average streamflow (USGS, 2017), the region experienced the most severe drought in record during the years 1958–1970. Following this unusually long drought, the 1970s were wetter than normal, registering some of the largest, historical flood events in the region (USGS, 2017). This is borne out in Fig. 5c with the sub-period 1970–1973 showing the largest $\langle R \rangle$. In contrast, the last two sub-periods (i.e., 1978–1981 and 1982–1985) were affected by conditions somewhat drier than normal

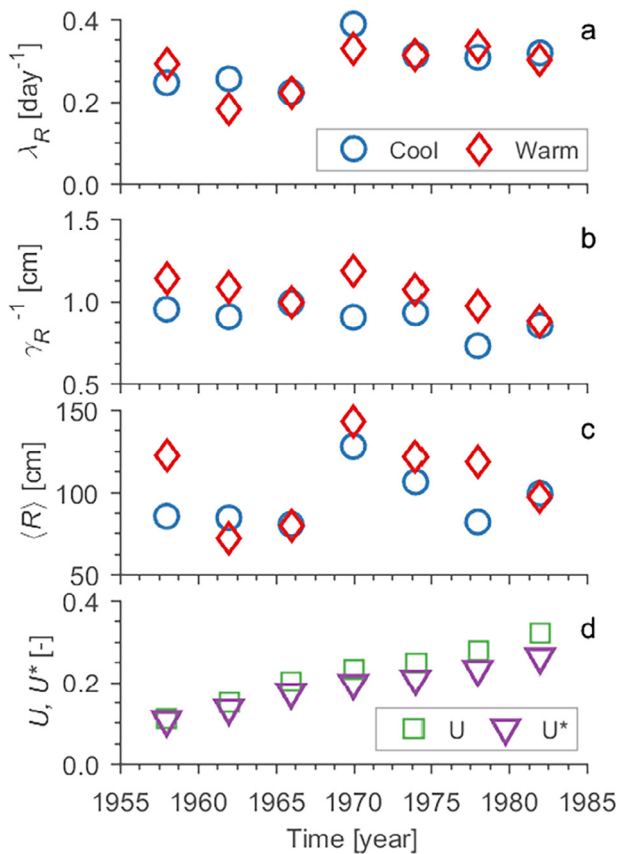


Fig. 5. (a) Mean rainfall frequency, λ_R ; (b) mean daily rainfall, γ_R^{-1} ; (c) mean annual rainfall, $\langle R \rangle$; and (d) fraction of impervious area, U , and fraction of effective impervious area, U^* , as a function of time for both the cool and warm season. The parameters were estimated using a 4-year time window over which the parameter values are considered to be constant.

(USGS, 2017).

The fraction of effective impervious area, U^* , shows steady climbing with increasing time. It increases from 0.1 at the beginning of the period of analysis to 0.27. As expected, the impervious fraction in the watershed, U , shows the same trend as U^* since the variables are linearly related according to $U^* = \beta U + \alpha$. The values of β and α were found equal to 0.745 and 0.024, respectively. The value of β indicates that $\sim 75\%$ of the impervious area in the watershed is connected to the watershed outlet, thereby directly contributing surface runoff to the streamflow Q . The value of 0.024 found for α suggests only a mild tendency for the pervious areas in the watershed to directly contribute surface runoff.

The parameters for the mean response time of effective pervious, k_p^{-1} , and impervious, k_i^{-1} , areas are shown in Fig. 6a and b, respectively. k_p^{-1} varies from ~ 10 to 60 days, with the mean value being ~ 37 days including both the cool and warm season (Fig. 6a). Indeed, k_p^{-1} shows a similar level of variability in both seasons and does not reveal a considerable trend with respect to time. Likewise, k_i^{-1} does not reveal any marked trends, varying randomly between ~ 0.04 and 0.16 days (~ 1 to 4 h) (Fig. 6b), with the mean value, including both seasons, being ~ 0.08 days (~ 2 h). Note that there is nearly two orders of magnitude difference between the mean k_i^{-1} and k_p^{-1} , reflecting the fast response of surface runoff versus the slow subsurface response of baseflow.

The last two parameters in the SMM are the mean frequency of stormwater runoff, λ_p , and subsurface recharge, λ_i , events. λ_i was set equal to λ_R , meaning that every rainfall event contributes to surface runoff. λ_p (not shown) behaves similarly to k_p , e.g., the correlation between the two parameters is high, ~ 0.96 . In this subsection, we have

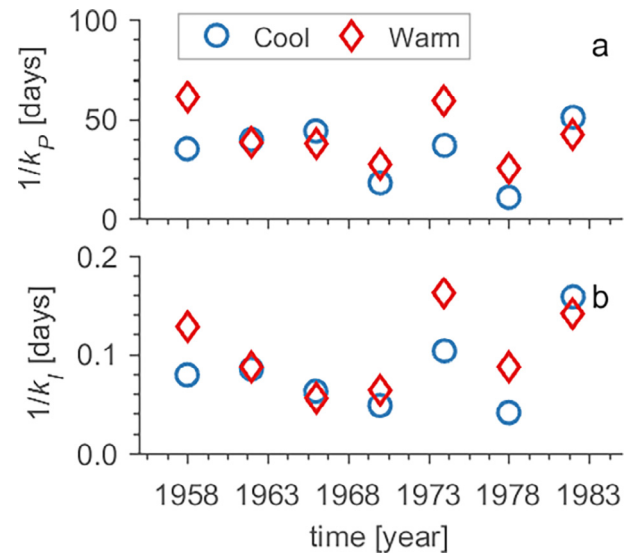


Fig. 6. Parameter estimates as a function of time for both the cool and warm season: Mean response time of the (a) pervious, $1/k_p$, and (b) impervious, $1/k_i$, area in the watershed. The parameters were estimated using a 4-year time window over which the parameter values are considered to be constant.

carefully explained the behavior of the SMM parameters and demonstrated that the parameters can be reliably estimated from available data. The parameter estimation approach employed can be implemented with relative ease in any other watershed. This is an advantage of the SMM that could be beneficial to urban planners and stormwater managers facing increasingly reduced budgets for long-term monitoring and modeling studies. Now that all the parameter values have been determined, in the next subsections we apply the SMM to perform the flow regime attribution.

4.3. Flow regime attribution with indicators of hydrological alteration

To perform the flow regime attribution, i.e., to distinguish the impacts of climate variability from those associated with landscape change, we use the streamflow indicators defined in Section 2.4, namely $\langle Q \rangle$, $\text{var}(Q)$, $s(Q)$, h , and C . We compute these indicators under three different scenarios. In the first scenario, S1, both the urbanization and the climate parameters are allowed to change with respect to time when simulating streamflow with the SMM. The purpose with S1 is to capture the dynamic interactions between urbanization and climate as they unfold in time. The second scenario, S2, simulates streamflow by fixing urbanization to the level at the onset of the streamflow record, $U = 0.1$, while the climate parameters are allowed to vary with time. The purpose with S2 is to isolate the impact of climate on the flow regime. The last scenario, S3, simulates streamflow by assuming average rainfall conditions while urbanization is allowed to change in time. The purpose with S3 is to isolate the effect of urbanization on the flow regime. By contrasting the three scenarios, we try to clarify whether climate and/or urbanization is driving the temporal trends in streamflow. In addition, for all the scenarios, the parameters k_i^{-1} , k_p^{-1} , and λ_p are fixed; they are set equal to their average values, as they did not show any dependence on time. The parameter λ_i is set equal to λ_R .

To compute $\langle Q \rangle$, $\text{var}(Q)$, and $s(Q)$, the equations previously derived from the SMM approach are used (see Appendix). In the case of h and C , the SMM is first used to simulate 100-year long time series of daily streamflow for each sub-period of analysis. Then, the time series are used to estimate h and C following the approaches by Jovanovic, García, et al. (2016a); Jovanovic, Mejía, et al. (2016b). To minimize additional complexity in the variables, we focus now the analysis on the cool season.

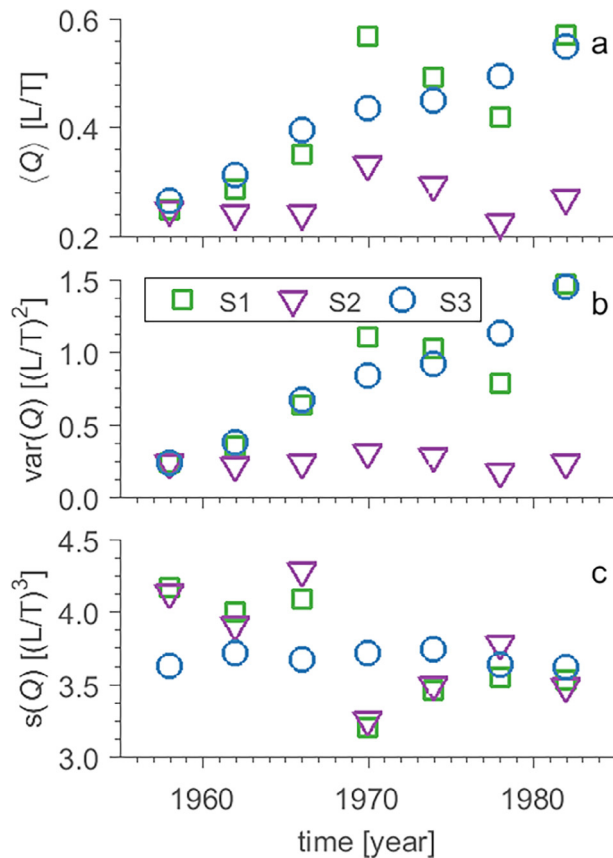


Fig. 7. Streamflow indicators of hydrological alteration as a function of time: (a) Mean, $\langle Q \rangle$; variance, $\text{var}(Q)$; and skewness, $s(Q)$, of streamflow. The indicators are shown for three different scenarios representing the joined impacts of climate and urbanization (S1), only climatic impacts (S2), and only urbanization impacts (S3). For S2, urbanization is set constant to the value at the beginning of the gauging period, while for S3 the climate parameters (i.e., λ_R and γ_R^{-1}) are set equal to their mean values and urbanization varies with time.

For S1 (climate + urban) in Fig. 7a, $\langle Q \rangle$ increases steadily with time. Contrasting S1 (climate + urban) against both S2 (only climate) and S3 (only urban) (Fig. 7a), it is apparent that the temporal trend in $\langle Q \rangle$ is due to increasing urbanization (i.e., the climate + urban scenario, S1, and the only urban scenario, S3, show similar trends). This simply means that as urbanization increases additional surface runoff is generated, augmenting $\langle Q \rangle$. In fact, this was expected from the plots of the parameter values (Fig. 5), which show that U^* increases with time (Fig. 5d) but the rainfall parameters do not (Fig. 5a and b). Here climate variability tends mostly to dampen the impacts of urbanization (i.e., the only urban scenario, S3, tends to be greater than the climate + urban scenario, S1), except for the unusually wet period of 1970–1973 where climate clearly amplifies $\langle Q \rangle$. Likewise, the temporal trend for $\text{var}(Q)$ (Fig. 7b) is driven by urbanization (i.e., the climate + urban scenario, S1, and the only urban scenario, S3, show similar behavior). This also indicates increase streamflow flashiness with time since $\text{var}(Q)$ measures the variability of Q . As was the case with $\langle Q \rangle$, climate tends to dampen the effect of urbanization on $\text{var}(Q)$.

The behavior is different for $s(Q)$ where the tendency is for S1 (climate + urban) and S2 (only climate) to mimic each other, while S3 (only urban) shows little change with time (Fig. 7c). The former means that, in contrast with $\langle Q \rangle$ and $\text{var}(Q)$, climate tends to drive the changes in the skewness, not urbanization. The skewness does not show an evident temporal trend, instead it seems to shift from a value of ~ 4 , prior to the year 1970, to a value of 3.5 after that year. Thus, the mean and variance are useful for distinguishing the impacts of climate and urbanization on streamflow, while the skewness is mostly affected by

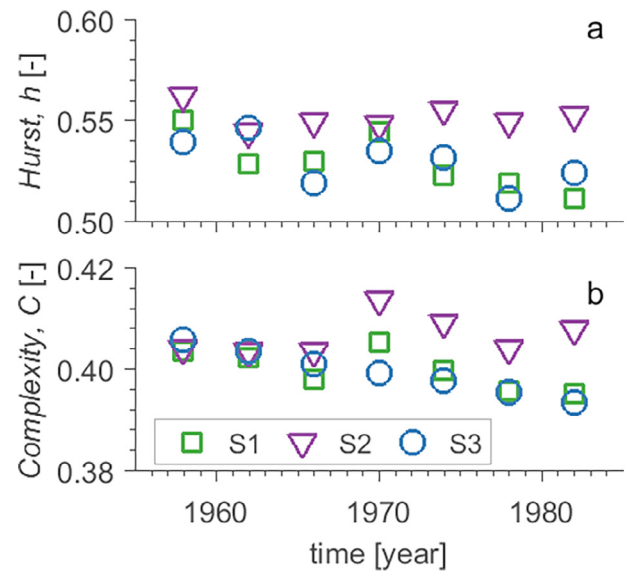


Fig. 8. Streamflow indicators of hydrological alteration as a function of time: (a) Hurst exponent, h ; and streamflow complexity measure, C . The indicators are shown for three different scenarios representing the joined impacts of climate and urbanization (S1), only climatic impacts (S2), and only urbanization impacts (S3). For S2, urbanization is set constant to the value at the beginning of the gauging period, while for S3 the climate parameters (i.e., λ_R and γ_R^{-1}) are set equal to their mean values and urbanization varies with time.

climate.

The behavior for the other two streamflow indicators, the Hurst exponent h (Fig. 8a) and complexity measure C (Fig. 8b), is similar to that of $\langle Q \rangle$ and $\text{var}(Q)$. S1 (climate + urban) and S3 (only urban) exhibit a similar temporal trend, while S2 (only climate) reflects the temporal climate fluctuations marked by dry and wet sub-periods. Additionally, these results are in agreement with previous empirical results that show that both h and C decline with increasing urbanization (Jovanovic et al., 2016a; Jovanovic, Mejía, et al., 2016b). The reduction in h means that, as the watershed becomes more urbanized, the streamflow record tends to resemble rainfall (white noise) by losing its long-range correlation.

Following from this observation, the loss of complexity in Fig. 8b means that the streamflow record becomes less structured with increasing urbanization. Interestingly, C captures quite well the climate fluctuations with the only climate scenario (S2) in Fig. 8b, suggesting that complexity is an effective indicator for separating the effects of climate and urbanization on streamflow.

From the implementation of the selected metrics, it is seen that the temporal trend of the flow regime in the Watts Branch watershed is mainly due to increasing urbanization while climate variability mainly imprints the impacts of dry and wet years on the temporal trend. Such imprinting is, nonetheless, important as it can clearly dampen or amplified the landscape (urbanization) effects. In addition, we can use the scenarios to estimate the change in the indicators that can be attributed to the climate or urban growth drivers. In this case, the values of $\langle Q \rangle$ and $\text{var}(Q)$ at the end of the gauging period are 2 and 7 times, respectively, larger than their values for the climate only scenario (S2).

4.4. Flow regime attribution with parameter sensitivity analysis

We use the SMM approach here to perform flow regime attribution with parameter sensitivity analysis. Note that parameter sensitivity analysis can be used in this case to inform the attribution process because the SMM allows to simultaneously and directly control both drivers of hydrological change: urban growth and climate. This facilitates separating the sensitivity analysis into climate- and urbanization-

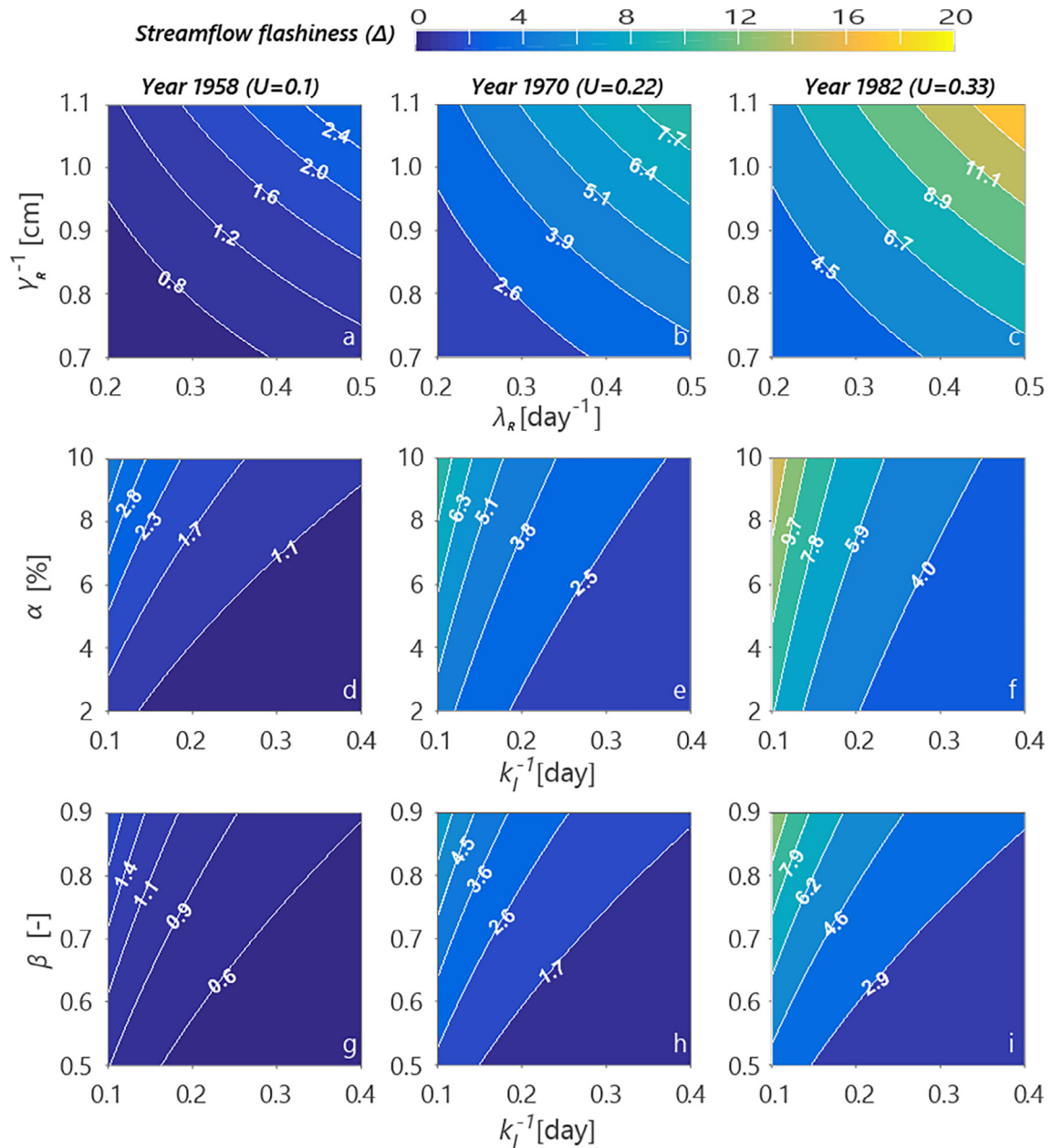


Fig. 9. Sensitivity of the streamflow flashiness to the rainfall, urbanization, and stormwater management parameters: (a–c) γ_R^{-1} versus λ_R , (d–f) α versus k_I^{-1} , and (g–i) β versus k_I^{-1} . From left to right, the columns represent increasing levels of urbanization U : 0.1 (urbanization at the start of the gauging period in year 1958), 0.22 (year 1970), and 0.33 (year 1982). The streamflow flashiness is computed as the ratio of the $\text{var}(Q)$ to $\text{var}(Q_{\text{pre}})$, i.e., the predevelopment $\text{var}(Q)$. $\text{var}(Q_{\text{pre}})$ is computed using average values for all the parameter values, except for urbanization which is set equal to the value at the beginning of the gauging period ($U = 0.1$).

related parameters. In contrast, in other watershed modeling approaches, the climate is normally treated as an external input to the model that cannot be directly controlled. Specifically, we assess the potential effect of climate, urbanization, and stormwater management on streamflow flashiness (Fig. 9). Streamflow flashiness is selected because this is a common metric used in practice to quantify stream quality in urban watersheds. To this end, we evaluate the sensitivity of the $\text{var}(Q)$ to the SMM parameter values associated with climate (γ_R^{-1} and λ_R), urbanization (α and β), and stormwater management (k_I^{-1}). For different combinations of the parameter values, we plot in Fig. 9

$$\Delta = \frac{\text{var}(Q)}{\text{var}(Q_{\text{pre}})}, \quad (3)$$

where $\text{var}(Q_{\text{pre}})$ is the predevelopment $\text{var}(Q)$. $\text{var}(Q_{\text{pre}})$ is computed using average values for all the parameters, except for urbanization

which is set equal to the value at the beginning of the gauging period ($U = 0.1$). For each panel in Fig. 9, $\text{var}(Q)$ is computed by changing two parameter values at a time while holding the other parameters values constant. The value of $\text{var}(Q_{\text{pre}})$ remains the same across all the panels in Fig. 9. Also, notice that each column in Fig. 9 represents at different level of urbanization, from left to right U is equal to 0.1 (urbanization at the start of the gauging period in year 1958), 0.22 (year 1970) and 0.33 (year 1982).

The effect of climate on streamflow flashiness is apparent in Fig. 9a–c. For a set level of stormwater management (fixed k_I^{-1} value), as both climate parameters (γ_R^{-1} and λ_R) are increased, Δ tends also to increase. This effect is amplified as urbanization increases, e.g., the values of Δ are much greater in Fig. 9c than in Fig. 9a for a chosen pair of parameter values. It is also interesting to note that, for the parameter ranges shown in Fig. 9, Δ seems equally affected by γ_R^{-1} and λ_R , i.e., the

contour lines in Fig. 9a–c do not deviate drastically from linearity. This means that changes in the magnitude of rainfall events are as important as changes in the frequency or number of events per year.

To assess the effect of urbanization and stormwater management conditions on Δ , we use the parameters α , β , and k_f^{-1} . β and k_f^{-1} can evidently have a strong effect on streamflow flashiness while the role played by α is less obvious. We include the parameter α since it affects the value of U^* , recall that $U^* = \beta U + \alpha$. Thus, by setting $U = 0$, α can be interpreted as representing the initial, average tendency of the watershed to generate surface runoff. Thus, different values of α may represent different initial land cover conditions.

Fig. 9d–f show the values of Δ for different combinations of k_f^{-1} and α . As anticipated, when the capacity of urban areas to store water increases (i.e., as k_f^{-1} increases), streamflow flashiness is reduced for a set value of α . A notable feature in Fig. 9d–f is that, for a given level of Δ , k_f^{-1} changes less as urbanization increases. This can be seen by comparing Fig. 9d and f, e.g., notice that in Fig. 9f the contour lines appear more vertical than in Fig. 9d. This means that as urbanization increases the effect of the initial land cover condition, α , on streamflow flashiness diminishes while stormwater management, k_f^{-1} , becomes the controlling factor. In contrast, stormwater management seems to play different roles with respect to the level of connectivity, β , in the watershed (Fig. 9g–i). In the case of a fast stormwater response time (e.g., $k_f^{-1} < 0.15$ days in Fig. 9g–i), stormwater management is the controlling factor (i.e., streamflow flashiness is more sensitive to k_f^{-1} than β). As the stormwater response time slows down, both factors, k_f^{-1} and β , become important in controlling streamflow flashiness. This seems to be somewhat independent of the level of urbanization in the watershed. For instance, notice that the contour lines are qualitatively similar between Fig. 9g and i.

5. Discussion

In urban watersheds, climate variability and urbanization act concurrently to alter and shape the streamflow dynamics. In turn, alterations to the flow regime can have substantial consequences on stream and riparian ecosystems. In trying to address the impact of urbanization on streamflow, the question arises as to how much of the observed impact may be due to urbanization versus climate variability and change. To answer this question, we proposed here the concept of flow regime attribution, in analogy to the event attribution practiced by the climate science community. The goal with flow regime attribution is to disentangle the impacts of climate variability and anthropogenic landscape change, urbanization in this case, on streamflow using both historical observations and modeling. We used in this study the SMM to perform the flow regime attribution. We discuss next the strengths, implications for sustainable urban development and stormwater management, implications for projecting hydrological change, applicability, and limitations of the SMM.

5.1. Strengths of the SMM

A strength of the SMM approach is to facilitate the estimation of streamflow indicators of hydrological alteration (e.g., the mean and variance of streamflow) that depend on the model parameters (e.g., Fig. 7). That is, the equations in the Appendix allow estimating indicators as a function of the parameter values used by the SMM. This, we believe, makes the attribution process more straightforward and, more importantly, allows relating the attribution to specific changes in the parameters, thereby ingesting physical meaning into the attribution process. The SMM also facilitates determining hydrological indicators that are less commonly used as their determination requires having long records, e.g., the Hurst exponent and complexity measure (Fig. 8).

Furthermore, the parameter parsimony of the SMM can be useful for assessing flow regimes and estimating hydrological indicators across multiple urban watersheds while maintaining data requirements to a

minimum. Implementing the model in multiple urban watersheds could help inform watershed planning and landscape decisions at the regional level, as opposed to focusing on one or few watersheds to make decisions, by identifying how impacts (changes in the hydrological indicators, e.g., the mean and variance of streamflow) may vary in a given metropolitan area. Additionally, implementing the model in different metropolitan areas could provide contrasting information on how different landscape decisions may have benefited (minimize changes to the flow regime) or not hydrological conditions. In our opinion, understanding the long-term implications of landscape decisions, in particular stormwater management decisions, is critical to ensure that evolving measures (e.g., from centralized detention ponds to decentralized low impact development) are guided towards beneficial goals. Part of the challenge here is that to quantify long-term changes to the flow regime requires long-term data and approaches. The SMM is specifically designed for such applications.

5.2. Implications for sustainable urban development and stormwater management

The SMM approach can be useful for informing sustainable urban development decisions. A central goal of sustainability is to ensure that impacts are not transferred across generations. Thus, to promote sustainable urban development, it is necessary to understand the effectiveness of urban stormwater management strategies over the long-term. Supportive of this goal, the SMM allows assessing the long-term effects of climate, urbanization, and stormwater management on streamflow. In addition, as part of sustainable urban stormwater management, the goals are often to increase green areas in urban watersheds through parks and other land uses, store and/or infiltrate excess runoff from urban areas, and disconnect upland impervious areas so that they do not discharge directly to the receiving stream network. The SMM approach can account for these factors at the watershed level and could be used to develop and evaluate different landscape and stormwater scenarios relevant to sustainable urban development. However, in the future, to make the SMM relevant to those applications, it is first necessary to better understand how the model parameters are affected by different stormwater management conditions. This could be achieved by implementing the model in urban watersheds with contrasting levels of stormwater management.

Another important goal of urban sustainability is to ensure human well-being and safety, e.g., by reducing flood risks. The SMM can be used to estimate flood potential at the outlet of an urban watershed using flood frequency analysis (Basso et al., 2016). Importantly, this means that the SMM could be used to estimate peak flows of any return period without having to rely on design storms. We think this is an important benefit of the SMM because design storms are characterized by large uncertainties. However, for this to be broadly useful to urban planners and stormwater managers, one needs to translate the daily peak flows from the SMM into hourly peak flows. Several data-driven approaches have been proposed to perform such translation (e.g., Ding, Wallner, Müller, & Haberlandt, 2016); any of those approaches could be used jointly with the SMM, as they tend to operate on daily streamflow time series data. Relevantly, this could also allow using the SMM to inform the design of individual stormwater management features (e.g., detention ponds or grass swales) which require as a key design input peak flows of a given return period. Further, the SMM could be readily extended to consider water pollutants such as total nitrogen and total suspended sediments following a similar stochastic approach as that of Daly, Bach, and Deletic (2014). This could be particularly relevant to help address increasing policy and regulatory requirements for reducing nutrient exports from urban watersheds.

5.3. Implications for projecting hydrological change from future climate and urban growth

The climate (rainfall) data in this study did not exhibit any trends, only shifts between wet and dry rainfall periods. Urban growth was the dominant driver of flow regime change. Nonetheless, the effects of trends in both rainfall and urban growth can be easily accounted for by the SMM. Any trends in the magnitude and/or frequency of rainfall can be captured by the parameters γ_R^{-1} and λ_R , respectively. Indeed, these parameters are commonly used to assess rainfall trends in climate studies.

Further, it is generally challenging to explore the implications for urban watersheds of future projected climate because projected climate data are typically coarse relative to the size of urban watersheds. Also, projected climate data need to be bias-corrected and downscaled which can result in large uncertainties at the spatial scale of urban watersheds. The SMM facilitates exploring the effects of climate and urban growth on hydrological change by allowing to vary these two drivers in an objective manner. For example, a range of hypothetical trends could be assigned to these drivers to evaluate their potential influence on flow regimes. The magnitude and range of the trends could be taken from regional climate and planning assessment studies. In this way, one could perform preliminary assessments about the likely effects of these trends with a minimum of information. Moreover, in cases where data relating hydrological indicators to stream ecological metrics exist, the SMM could potentially be used to address stream health change. The SMM is able to support such analysis by allowing to reliably compute flow regimes for urban watersheds.

5.4. Applicability of the SMM to other urban watersheds

Although our flow regime attribution with the SMM relied on a single watershed, we foresee the approach can be readily implemented in other urban watersheds. Past applications of SMMs have demonstrated their ability to successfully represent streamflow dynamics in a variety of landscape and climatic conditions (Doulatyari et al., 2015; Mejía et al., 2014). The minimum requirements for the SMM are daily rainfall and streamflow, and annual land cover change over time for major land cover classes. Although these data are available in the U.S., in other geographic settings it may be challenging to apply the model. In particular, data depicting annual land cover change over time may be difficult to obtain. In those cases, satellite proxy data could potentially be used. Further, the ability to transfer model parameters from one geographic region to another, with similar watershed and urban characteristics, could be explored in the future when trying to apply the SMM to data scarce regions.

5.5. Limitations of the SMM

A limitation of the SMM approach is that it does not explicitly account for the full, internal, spatial variability of urban watershed

conditions. For example, it accounts only for two land cover classes, pervious and impervious, and uses a single parameter, $1/k_i$, to represent the stormwater storage capacity of urban areas. In the future, the SMM could be further generalized to facilitate a more spatially distributed implementation. Also, future efforts could further explore the baseflow component of the model as this can be an important source of modeling uncertainty (Bhaskar & Welty, 2012; Bhaskar, Welty, Maxwell, & Miller, 2015). Nonetheless, the SMM can be a valuable tool for planning studies that may require long time horizons, and to perform watershed-level assessments of the distinct impacts of climate and urban growth on streamflow. The latter is likely to become increasingly important as the effects of climate continue to increase across the globe.

6. Conclusions

In this study, we demonstrated the ability of the SMM to perform flow regime attribution using the Watts Branch watershed as case study. This application showed that the model is able to represent the changing behavior of flow regimes in an urban watershed under conditions of nonstationarity. The nonstationarity was in this case due to urban growth while the climate (rainfall) forcing mainly revealed shifts between wet and dry periods. Nonetheless, in future applications of the SMM, a rainfall trend could be considered through changes in the rainfall parameters, λ_R and γ_R , with time. We also showed that the model parameters (9 out of the 11) can be readily estimated from available data, which is an advantage of the SMM that can facilitate its implementation across urban watersheds. This, in turn, could allow urban planners to assess whether hydrological changes in large metropolitan areas are dominated by urban growth, climate, or both.

We showed that the SMM can be used to separate the effects of climate and urban growth on flow regimes. This was done by analyzing the behavior of the model parameters with respect to time, determining streamflow indicators under different scenarios, and performing sensitivity analysis. The SMM has several beneficial features that support carrying out these analyses in a manner that is suitable for attribution: streamflow indicators (e.g., the mean, variance, and skewness of streamflow) that are a function of the model parameters are available, long streamflow time series can be easily simulated, and the drivers of urban growth and climate can be directly controlled. These features make the SMM attractive to perform preliminary assessments of the impacts of climate and urban growth on urban watersheds. They could also be used to test the response of flow regimes in urban watersheds to different scenarios involving urban growth, climate trends, and stormwater management at the watershed level. We believe such information could be useful to urban planners and decision makers.

Acknowledgements

The last author acknowledges support provided by the U.S. National Science Foundation, through Grant No. 1140070, to be a member of the Urban Sustainability Research Coordination Network.

Appendix: Mean, variance and skewness of streamflow as indicators of hydrological alteration

Using the SMM in Eq. (1), following the approach by Mejía et al. (2014), the first raw moment of the streamflow Q (mean of Q or $\langle Q \rangle$ [L^3/T]), as well as the second (variance of Q or $\text{var}(Q)$ [L^6/T^2]) and third (skewness of Q or $s(Q)$ [L^3/T^3]) central moments of Q can be computed as follows:

$$\langle Q \rangle = \frac{\lambda_p}{\gamma_R} A(1-U^*) + \frac{\lambda_f}{\gamma_R} AU^*, \quad (4)$$

$$\text{var}(Q) = \frac{\lambda_p k_p [(1-U^*)A]^2}{\gamma_R^2} + \frac{\lambda_f k_f (AU^*)^2}{\gamma_R^2} + \frac{2\lambda_p k_f k_p A^2 U^* (1-U^*)}{\gamma_R^2} \left[\frac{\gamma_R d_p + 2}{k_f + k_p} \right], \quad (5)$$

and

$$s(Q) = \frac{\langle Q - \langle Q \rangle \rangle^3}{\text{var}(Q)^{3/2}}, \quad (6)$$

where the third central moment of Q , $\langle Q - \langle Q \rangle \rangle^3 [(L/T)^3]$, is as follows:

$$\langle Q - \langle Q \rangle \rangle^3 = \frac{2\lambda_P k_P^2 A^3 (1-U)^3}{\gamma_R^3} + \frac{2\lambda_I k_I^2 A^3 U^3}{\gamma_R^3} + \frac{3\lambda_P k_I k_P A^3 U (1-U)}{\gamma_R^3} \left[\frac{2k_P (1-U)(3 + d_P \gamma_R)}{(k_I + 2k_P)} + \frac{k_I U (6 + 4d_P \gamma_R + d_P^2 \gamma_R^2)}{(2k_I + k_P)} \right]. \quad (7)$$

All the parameters in Eqs. (4)–(7) were previously defined (see Table 1 for a summary). Note that after estimating the parameter values following the approach outlined in Section 2.2, the parameters can then be used to determine the values of $\langle Q \rangle$, $\text{var}(Q)$, and $s(Q)$ using Eqs. (4)–(7).

References

- Baker, D. B., Richards, R. P., Loftus, T. T., & Kramer, J. W. (2004). A new flashiness index: Characteristics and applications to Midwestern rivers and streams. *Journal of the American Water Resources Association*, 40(2), 503–522.
- Bartlett, M. S., Daly, E., McDonnell, J. J., Parolari, A. J., & Porporato, A. (2015). Stochastic rainfall-runoff model with explicit soil moisture dynamics. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Science*, 471(2183).
- Basso, S., Schirmer, M., & Botter, G. (2015). On the emergence of heavy-tailed streamflow distributions. *Advances in Water Resources*, 82, 98–105.
- Basso, S., Schirmer, M., & Botter, G. C. G. (2016). A physically based analytical model of flood frequency curves. *Geophysical Research Letters*, 43(17), 9070–9076.
- BayLand (2015). Final Watts Branch watershed assessment, Rockville, Maryland.
- Beighley, R. E., & Moglen, G. E. (2003). Adjusting measured peak discharges from an urbanizing watershed to reflect a stationary land use signal. *Water Resources Research*, 39(4), 1093.
- Bhaskar, A. S., & Welty, C. (2012). Water Balances along an Urban-to-Rural Gradient of Metropolitan Baltimore, 2001–2009. *Environmental & Engineering Geoscience*, 18(1), 37–50.
- Bhaskar, A. S., Welty, C., Maxwell, R. M., & Miller, A. J. (2015). Untangling the effects of urban development on subsurface storage in Baltimore. *Water Resources Research*, 51(2), 1158–1181.
- Bindoff, N. L., Stott, P. A., AchutaRao, K. M., Allen, M. R., Gillett, N., Gutzler, D., et al. (2013). Detection and Attribution of Climate Change: from Global to Regional. *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press.
- Botter, G., Basso, S., Porporato, A., Rodriguez-Iturbe, I., & Rinaldo, A. (2010). Natural streamflow regime alterations: Dams of the Piave river basin (Italy). *Water Resources Research*, 46(6), W06522.
- Botter, G., Basso, S., Rodriguez-Iturbe, I., & Rinaldo, A. (2013). Resilience of river flow regimes. *Proceedings of the National Academy of Sciences*, 110(32), 12925–12930.
- Botter, G., Porporato, A., Daly, E., Rodriguez-Iturbe, I., & Rinaldo, A. (2007a). Probabilistic characterization of base flows in river basins: Roles of soil, vegetation, and geomorphology. *Water Resources Research*, 43(6), W06404.
- Botter, G., Porporato, A., Rodriguez-Iturbe, I., & Rinaldo, A. (2007b). Basin-scale soil moisture dynamics and the probabilistic characterization of carrier hydrologic flows: Slow, leaching-prone components of the hydrologic response. *Water Resources Research*, 43(2), W02417.
- Botter, G., Porporato, A., Rodriguez-Iturbe, I., & Rinaldo, A. C. W. (2009). Nonlinear storage-discharge relations and catchment streamflow regimes. *Water Resources Research*, 45(10), W10427.
- Brown, L. R., Cuffney, T. F., Coles, J. F., Fitzpatrick, F., McMahon, G., Steuer, J., et al. (2009). Urban streams across the USA: Lessons learned from studies in 9 metropolitan areas. *Journal of the North American Benthological Society*, 28(4), 1051–1069.
- Byrd, R., Hribar, M., & Nosedal, J. (1999). An interior point algorithm for large-scale nonlinear programming. *SIAM Journal on Optimization*, 9(4), 877–900.
- Carter, T., Jackson, C. R., Rosemond, A., Pringle, C., Radcliffe, D., Tollner, W., et al. (2009). Beyond the urban gradient: barriers and opportunities for timely studies of urbanization effects on aquatic ecosystems. *Journal of the North American Benthological Society*, 28(4), 1038–1050.
- Ceola, S., Botter, G., Bertuzzo, E., Porporato, A., Rodriguez-Iturbe, I., & Rinaldo, A. C. W. (2010). Comparative study of ecohydrological streamflow probability distributions. *Water Resources Research*, 46(9), W09502.
- CRDPW (2001). Watts Branch watershed study and management plan final report, City of Rockville Department of Public Works, City of Rockville.
- Daly, E., Bach, P. M., & Deletic, A. (2014). Stormwater pollutant runoff: A stochastic approach. *Advances in Water Resources*, 74, 148–155.
- Ding, J., Wallner, M., Müller, H., & Haberlandt, U. (2016). Estimation of instantaneous peak flows from maximum mean daily flows using the HBV hydrological model. *Hydrological Processes*, 30(9), 1431–1448.
- Doulatyari, B., Betterle, A., Basso, S., Biswal, B., Schirmer, M., & Botter, G. (2015). Predicting streamflow distributions and flow duration curves from landscape and climate. *Advances in Water Resources*, 83, 285–298.
- Frumkin, H. (2002). Urban sprawl and health. *Public Health Reports*, 117(3), 201–217.
- Gallo, C., Moore, A., & Wywrot, J. (2012). Comparing the adaptability of infiltration based BMPs to various U.S. regions. *Landscape and Urban Planning*, 106(4), 326–335.
- Geneletti, D., La Rosa, D., Spyra, M., & Cortinovis, C. (2017). A review of approaches and challenges for sustainable planning in urban peripheries. *Landscape and Urban Planning*, 165, 231–243.
- Homer, C. G., Dewitz, J. A., Yang, L., Jin, S., Danielson, P., Xian, G., et al. (2015). Completion of the 2011 National Land Cover Database for the conterminous United States-Representing a decade of land cover change information. *Photogrammetric Engineering and Remote Sensing*, 81(5), 345–354.
- Johnson, M. (2001). Environmental impacts of Urban Sprawl: A survey of the literature and proposed research Agenda. *Environment and Planning A: Economy and Space*, 33(4), 717–735.
- Jovanovic, T., García, S., Gall, H., & Mejía, A. (2016a). Complexity as a streamflow metric of hydrologic alteration. *Stochastic Environmental Research and Risk Assessment*, 1–13.
- Jovanovic, T., Mejía, A., Gall, H., & Gironás, J. (2016b). Effect of urbanization on the long-term persistence of streamflow records. *Physica A: Statistical Mechanics and its Applications*, 447, 208–221.
- Kantelhardt, J. W., Koscielny-Bunde, E., Rybski, D., Braun, P., Bunde, A., & Havlin, S. (2006). Ong-term persistence and multifractality of precipitation and river runoff records. *Journal of Geophysical Research: Atmospheres*, 111(D1), D01106.
- Lamberti, P. W., Martin, M. T., Plastino, A., & Rosso, O. A. (2004). Intensive entropic non-triviality measure. *Physica A: Statistical Mechanics and its Applications*, 334(1–2), 119–131.
- Lee, J., & Heaney, J. (2003). Estimation of urban imperviousness and its impacts on storm water systems. *Journal of Water Resources Planning and Management*, 129(5), 419–426.
- Leopold, L. B. (1968). Hydrology for urban land planning – A guidebook on the hydrologic effects of urban land use. In: *Geological Survey Circular 554*, U.S. Geological Survey, Washington D.C., (pp. 18).
- López-Ruiz, R., Mancini, H. L., & Calbet, X. (1995). A statistical measure of complexity. *Physics Letters A*, 209(5), 321–326.
- Martin-Mikle, C. J., de Beurs, K. M., Julian, J. P., & Mayer, P. M. (2015). Identifying priority sites for low impact development (LID) in a mixed-use watershed. *Landscape and Urban Planning*, 140, 29–41.
- MCDEP (2003). *Watts Branch: Watershed restoration study*, Montgomery County, Maryland.
- Mejía, A., Daly, E., Rossel, F., Jovanovic, T., & Gironás, J. (2014). A stochastic model of streamflow for urbanized basins. *Water Resources Research*, 50(3), 1984–2001.
- Mejía, A., Rossel, F., Gironás, J., & Jovanovic, T. (2015). Anthropogenic controls from urban growth on flow regimes. *Advances in Water Resources*, 84, 125–135.
- Miltner, R. J., White, D., & Yoder, C. (2004). The biotic integrity of streams in urban and suburbanizing landscapes. *Landscape and Urban Planning*, 69(1), 87–100.
- National Academies of Sciences, E., & Medicine (2016). *Attribution of Extreme Weather Events in the Context of Climate Change*, The National Academies Press, Washington, DC, (pp. 186).
- Poff, N. L., Richter, B. D., Arthington, A. H., Bunn, S. E., Naiman, R. J., Kendy, E., et al. (2010). The ecological limits of hydrologic alteration (ELOHA): A new framework for developing regional environmental flow standards. *Freshwater Biology*, 55(1), 147–170.
- Poff, N. L., & Zimmerman, J. K. H. (2010). Ecological responses to altered flow regimes: A literature review to inform the science and management of environmental flows. *Freshwater Biology*, 55(1), 194–205.
- Postel, S., & Richter, B. (2003). *Rivers for life: Managing water for people and nature*. Washington D.C.: Island Press 253.
- Pyke, C., Warren, M. P., Johnson, T., LaGro, J., Jr, Scharfenberg, J., Groth, P., et al. (2011). Assessment of low impact development for managing stormwater with changing precipitation due to climate change. *Landscape and Urban Planning*, 103(2), 166–173.
- Roy, A. H., & Shuster, W. D. (2009). Assessing impervious surface connectivity and applications for watershed management. *JAWRA Journal of the American Water Resources Association*, 45(1), 198–209.
- Sharley, D. J., Sharp, S. M., Marshall, S., Jeppe, K., & Pettigrove, V. J. (2017). Linking urban land use to pollutants in constructed wetlands: Implications for stormwater and urban planning. *Landscape and Urban Planning*, 162, 80–91.
- Shuster, W. D., Pappas, E., & Zhang, Y. (2008). Laboratory-scale simulation of runoff response from pervious-impervious systems. *Journal of Hydrologic Engineering*, 13(9), 886–893.
- Sleeter, B. M., Sohl, T. L., Loveland, T. R., Auch, R. F., Acevedo, W., Drummond, M. A., et al. (2013). Land-cover change in the conterminous United States from 1973 to 2000. *Global Environmental Change*, 23(4), 733–748.
- Su, W., Gu, C., Yang, G., Chen, S., & Zhen, F. (2010). Measuring the impact of urban sprawl on natural landscape pattern of the Western Taihu Lake watershed, China. *Landscape and Urban Planning*, 95(1), 61–67.
- USGS (2017). Maryland and the District of Columbia: Floods and Droughts, <https://md.water.usgs.gov/publications/wsp-2375/md-dc/md-dc.html>, Accessed on April 12, 2017.
- Vimal, R., Geniaux, G., Pluvinet, P., Napoleone, C., & Lepart, J. (2012). Detecting threatened biodiversity by urbanization at regional and local scales using an urban sprawl simulation approach: Application on the French Mediterranean region. *Landscape and Urban Planning*, 104(3), 343–355.
- Wilson, B., & Chakraborty, A. (2013). The environmental impacts of Sprawl: Emergent themes from the past decade of planning research. *Sustainability*, 5(8).
- Wu, H., Bolte, J. P., Hulse, D., & Johnson, B. R. (2015a). A scenario-based approach to integrating flow-ecology research with watershed development planning. *Landscape and Urban Planning*, 144, 74–89.
- Wu, J., Stewart, T. W., Thompson, J. R., Kolka, R. K., & Franz, K. J. (2015b). Watershed features and stream water quality: Gaining insight through path analysis in a Midwest urban landscape, U.S.A. *Landscape and Urban Planning*, 143, 219–229.
- Yang, B., & Li, M.-H. (2011). Assessing planning approaches by watershed streamflow modeling: Case study of The Woodlands, Texas. *Landscape and Urban Planning*, 99(1), 9–22.